**Implementation and comparison of existing occupant behaviour models in EnergyPlus**

# H. Burak Gunay1, William O'Brien1, Ian Beausoleil-Morrison2

1Department of Civil and Environmental Engineering, Carleton University

2Department of Mechanical and Aerospace Engineering, Carleton University

**Abstract:**

To incorporate occupant behaviour in building performance simulation (BPS), researchers have developed a number of occupant behaviour and presence models based on long-term field observations. This paper describes the implementation of models from the literature for predicting occupancy and use of operable windows, blinds, lighting, and clothing for offices in the BPS tool EnergyPlus. In order to make the occupant models from the literature more widely available to researchers and practitioners, the EnergyPlus EMS scripts are made publicly available. The paper then presents a comparison of the model predictions based on a typical office and demonstrates how differences in these models influence BPS results. In general, the window, blinds, and lighting use model predictions vary significantly from model to another. Despite these significant variations, the BPS models with different occupant behaviour model combinations provided consistent load reduction predictions in response to design changes.

**Keywords:** Occupant behaviour, occupant behaviour models, building performance simulation, window use models, light use models, blinds use models

**Corresponding Author:** William O'Brien

**Main Address:**

Carleton University

Department of Civil and Environmental Engineering

1125 Colonel by Drive

Ottawa, Ontario, Canada K1S 5B6

Email: Liam\_OBrien@carleton.ca

Tel: +1 613 520 2600 x 8037

Fax: +1 613 520 3951

# Introduction

Office occupants, by interacting with just a few building components — such as windows, window blinds and lighting ­­— account for great uncertainty over a building's performance. It has been reported that occupant behavior can impact energy performance of offices by a factor of two or more (Norford et al. 1994; Reinhart 2004; Haldi and Robinson 2011; D'Oca and Hong 2014; Feng et al. 2015). The occupant interactions with these building components also influence commonly used comfort metrics in building performance simulation (BPS). For example, Reinhart et al. (2006) reported that the daylight autonomy 2.5 m away from the window in an office located in Vancouver, Canada can be as low as 30% and as high as 80% depending on the internal blinds position. A major challenge in making building designs robust against this uncertainty, as stated by Hong (2012), is to incorporate occupants' behaviour and presence realistically in the building performance simulation (BPS) tools.

# Problem definition

Occupant interacting components in BPS tools are currently represented in terms of static schedules — meaning that these schedules do not change from design to design nor do they from individual to individual (Hoes et al. 2009). For example, a BPS model with a poor fenestration design would input the identical lighting and blinds schedules as any other fenestration design (Deru et al. 2011). This implies that occupants are passive recipients of the indoor climate.

In reality, there should be a dynamic interaction between a building and its occupants. The construct of comfort affects the occupants' behaviour, and the occupants' behaviour affects the performance of buildings. Occupants often can adapt their indoor climate by interacting with lights, blinds, windows, and thermostats or they can adapt to the indoor climate by changing their clothing assembly or the type of activity (Haldi and Robinson 2008). In other words, different design and control alternatives studied in BPS models should result in unique schedules for lighting, blinds, window, thermostat, clothing and activity schedules. Because the static schedules fail to reflect these dynamic interactions between a building and its users, they do not necessarily promote better design alternatives.

# Background on occupant behaviour and presence modelling

Occupant models can mimic occupants' interactions with zone level building components (e.g., lights, blinds, windows) and with themselves (e.g., clothing insulation) (Clarke et al. 2006). They have been typically developed upon long-term observational studies. These models are high-level simplified renditions of the cause and predicted effect of different environmental conditions rather than cognitive models. There are several broad categories of modelling and simulation methods that exist in the literature.

The majority of the models have (or use) input explanatory variables to predict the likelihood of a state change. For example, Reinhart (2004)'s model predicts the likelihood of a light switch action and Haldi and Robinson (2010)'s model predicts the likelihood of a blinds opening or a blinds closing action. Because occupants in an office (as individuals or collective entities) are modelled as autonomous agents undertaking actions, these models are also known as agent-based models.

In general, the agent-based occupant models have been derived from a Markovian perspective; meaning that the state-transition probability depends on the current state only (Parys et al. 2011). When a Markovian occupant model is simulated as a discrete-time random process, it inputs the explanatory variables to provide the likelihood of a state-transition in the next time-step. For example, Haldi and Robinson (2010)'s blinds use model predicts the likelihood of an blinds closing action in the next five minutes by looking at the workplane illuminance and unshaded window fraction. Similarly, Haldi and Robinson (2009)'s window use model inputs the indoor and outdoor temperature to predict the likelihood of a window opening action in the next five minutes. However, limitations may arise due to the fact that this simulation approach requires a fixed and prescribed time-step (Gunay et al. 2014). Because a time-step is prescribed for each model, the time-step cannot change between simulations. Consequently, occupant models can become incompatible with each other or with building and HVAC component models which require different temporal resolutions.

When a Markovian occupant model is simulated as a discrete-event random process, it provides the likelihood of a state-transition in the next event-step. Often, the events were tied to an occupancy state change (Newsham 1994; Rijal et al. 2008; Haldi and Robinson 2011); i.e., time-step after arrival or time-step prior to departure. For example, Reinhart (2004)'s light switch model inputs workplane illuminance to predict the likelihood of a light switch action at arrival. Alternatively, the next event time can also be sampled from a survival function (Haldi and Robinson 2011). For example, Wang et al. (2005) computed the duration of an intermediate vacancy period (e.g., lunch break) from an exponential distribution. Similarly, Haldi and Robinson (2009) determined the duration that windows remain open based on a survival analysis.

As an alternative for the agent-based models, in a few cases occupant behaviour was represented as Bernoulli random processes. These models predict the probability of finding a zone level building component at a certain position. For example, Haldi and Robinson (2008)'s model provide the probability of finding a window open by looking at the indoor temperature.

# Motivation

If we could confidently and easily employ existing occupant models in the BPS-based design process, they could address the aforementioned issues arising from simple static scheduled behaviours. However, in only a few cases these occupant models have been implemented in BPS tools. Occupant presence and behaviour models are seldom used for compliance with building standards and code (e.g., ASHRAE Standard 90.1-2013 (ASHRAE 2013)). The literature points out two underlying reasons to explain the slow adoption of the occupant models by the BPS modellers.

(1) Questions about the accuracy and transferability of the occupant models:

A recent review paper (O'Brien and Gunay 2014) pointed out that the existing modelling methodologies are vastly fragmented such that their validity is uncertain depending on a significant number of contextual factors (e.g., differences in the use of shading devices and electrical lighting between shared and private office spaces (Newsham 1997; Reinhart and Voss 2003; Haldi and Robinson 2010) or the ease of using the control interfaces (e.g., motorized vs. manual blinds (Sutter et al. 2006))). However, perhaps due to the limited size of observed populations, these contextual factors have not been documented or acknowledged in many existing occupant models. As a consequence, the transferability of occupant models in other buildings have been questioned (O'Brien and Gunay 2014).

(2) Models are not accessible in BPS tools used for design and compliance checking:

Many of the occupant models in widely used BPS tools (e.g., EnergyPlus, ESP-r, and TRNSYS) are not available. Furthermore, the simulation platforms that permit the incorporation of custom component models (e.g., occupant models) in BPS tools are not mature enough to provide a standardized and user-friendly interface for the rapid implementation. For example, there is no debugging environment in the EMS application of EnergyPlus (LBNL 2013). The modellers need to go through a rudimentary trial and error procedure to identify even minor issues in their programs. Should the user wish to implement the occupant models in some other programming environment (e.g., Matlab), s/he would need to use a co-simulator such as MLE+ (Nghiem 2010) or Building Controls Virtual Test Bed (Wetter 2008) — at the very least this implies tackling issues arising due to version compatibilities with the BPS tool. Alternatively, the BPS users could incorporate the occupant models through source-code alterations in the BPS tools.

The contribution of this paper is to implement and compare existing occupant models using a generic shoebox model in EnergyPlus. A number of models predicting occupants' presence and behaviours in offices were selected from several review articles (Parys et al. 2011; Fabi et al. 2012; Gunay et al. 2013). Selected models were then transformed into a common simulation framework and they were implemented in the EMS application of the BPS tool EnergyPlus. We chose the EMS application because it was easier to implement than changing the EnergyPlus source-code, the code structure was transparent to the users, and the model library could be easily expanded or modified by the users. We undertook the code validation procedures described in ASHRAE Standard 140 (2011): (1) by checking the models against a previous version of themselves after making changes in a subroutine to ensure that only intended changes actually resulted; (2) by checking the models against themselves after a single algorithmic change to reveal the sensitivity between runs; (3) by diagnosing the algorithmic sources of prediction differences and by leaving internal dummy variables inside each if-then-else statement to analyze their response during the simulation. Selected models include light switch models (Hunt 1979; Reinhart 2004; Boyce et al. 2006), window use models (Haldi and Robinson 2008; Rijal et al. 2008; Yun and Steemers 2008; Haldi and Robinson 2009), window blind use models (Newsham 1994; Reinhart 2004; Haldi and Robinson 2010), a clothing insulation level model (Schiavon and Lee 2013) and occupant presence models (Reinhart 2004; Wang et al. 2005; Page et al. 2008). The EMS scripts (in the EnergyPlus Runtime Language ERL) — with comments explaining how to use the models in an EnergyPlus model — are also made available in the public domain as supplemental files.

In order to discuss the transferability of occupant models to other contexts, predictions made by different occupant models were compared with each other based on the repeated simulations of an office in Ottawa, Canada. The way these predictions influenced the heating, cooling, and lighting load calculations of a BPS tool was demonstrated, and these BPS results were contrasted to cases with static ASHRAE (2013) schedules. Based on this analysis, the limitations of existing occupant models were identified and future research recommendations were developed.

# Methodology

This section first provides an overview of the selected models by defining their fundamental differences in defining human behaviour in offices. This is followed by a subsection whereby the selected models were transformed into a common simulation framework. This subsection is intended to provide a layout for the current implementation. Then, the implementation in EMS application of EnergyPlus, in particular the BPS tool specific assumptions and limitations, was presented. This section also presents a simple office model through which the influence of the occupant models over BPS predictions was studied.

# An overview of the selected occupant models

Table 1 provides a summary of the selected occupant models, the source of the original model, and their predictors.

Table 1: An overview of the selected occupant models.

|  |  |  |
| --- | --- | --- |
| Models | Developers | Predictors |
| Light switch-On | Hunt (1979) | Workplane illuminance |
| Reinhart (2004) | (1) Workplane illuminance and (2) occupancy period |
| Light switch-Off | Reinhart (2004) | Duration of absence upon departure |
| Boyce et al. (2006) | Workplane illuminance |
| Blinds closing | Newsham (1994) | Transmitted direct solar irradiance |
| Reinhart (2004) | Workplane direct solar irradiance |
| Haldi and Robinson (2010) | (1) Workplane illuminance, (2) occupancy period, and (3) unshaded window fraction |
| Blinds opening | Newsham (1994) | Occupancy period |
| Reinhart (2004) | Occupancy period |
| Haldi and Robinson (2010) | (1) Workplane illuminance, (2) occupancy period, (3) unshaded window fraction, (4) outdoor illuminance |
| Window opening/closing | Rijal et al. (2008) | (1) Indoor temperature, (2) outdoor temperature, and (3) occupancy period |
| Haldi and Robinson (2008) | (1) Indoor temperature, (2) outdoor temperature |
| Haldi and Robinson (2009) | (1) Indoor temperature, (2) outdoor temperature, (3) occupancy period, and (4) rain |
| Yun and Steemers (2008) | (1) Indoor temperature, (2) outdoor temperature, and (3) occupancy period |
| Clothing | Schiavon and Lee (2013) | (1) Outdoor temperature in the morning and (2) operative temperature |
| Presence | Reinhart (2004) | (1) Normally distributed event times for arrival, coffee and lunch breaks, and departure and (2) Deterministic vacancy periods |
| Wang et al. (2005) | (1) Normally distributed event times for arrival, coffee and lunch breaks, and departure and (2) Exponentially distributed vacancy periods |
| Page et al. (2008) | (1) The profile of probability of presence during a week and (2) the parameter of mobility |

The light switch-on model developed by Hunt (1979) is one of the earliest occupant behaviour models. It attempts to predict occupants' light switch-on actions with the workplane illuminance. Lightswitch-2002, a more recent light switch-on model, was developed by Reinhart (2004). It also uses workplane illuminance as the primary predictor. Hunt (1979)'s light switch-on model, despite acknowledging it, does not incorporate the differences in occupants' light switch-on behaviour during different occupancy periods, whereas Reinhart (2004)'s light switch-on model incorporates this effect. In Reinhart (2004)'s model, occupants tend to switch on their lights at arrival rather than during intermediate occupancy period. This can be attributed to the fact that the stimulus gradient (from outdoors to indoors) is much higher at arrival and it is easier to access the controls at arrival (while the occupant is still standing). In Reinhart (2004), occupants are assumed to switch off lights at departure only. This implies that simulated occupants are not modelled to switch off their lights during intermediate occupancy, even when daylight is sufficient. Light switch-off behaviour prior to a departure is predicted by the duration of absence followed by the departure. On the contrary, in Boyce et al. (2006) light switch-off behaviour of occupants is predicted with the workplane illuminance. This implies that the occupants are modelled to be more responsive to the availability of daylight. Therefore, the modelling approaches for light switch-off by Reinhart (2004) and Boyce et al. (2006) portray office occupants at two different extremities: daylight unconscious and daylight responsive, respectively.

In Newsham (1994)’s blinds use model which was developed upon the data collected by Inoue (1988), the blinds closing actions are predicted with the transmitted direct solar irradiance; the simulated occupants are assumed to close their blinds when it exceeds 233 W.m-2. Reinhart (2004) suggests that occupants close their blinds, when the direct solar irradiance on the workplane (0.8 m above the floor level) exceeds 50 W.m-2. In Haldi and Robinson (2010), occupants' blinds closing action is predicted using two different multivariate models for two different occupancy periods (i.e. at arrival or during intermediate occupancy). In Newsham (1994) and Reinhart (2004), occupants are modelled to open their blinds only at arrival. The multivariate models by Haldi and Robinson (2010) permits blinds closing action at any occupied period. However, opening blinds at arrival is modelled to be more likely to occur than during intermediate occupancy. Blinds in Haldi and Robinson (2010)'s model are permitted to be partially open or closed, whereas in Newsham (1994)'s and in Reinhart (2004)'s models blinds are modelled as binary components (fully open or fully closed). No statistical model was found to predict slat angle use of venetian blinds (O'Brien et al. 2013).

In Rijal et al. (2008), Haldi and Robinson (2009), Yun and Steemers (2008), and Haldi and Robinson (2008) occupants' window opening and closing decisions are modelled to be primarily influenced by the indoor and outdoor temperatures. Furthermore, Haldi and Robinson (2009) incorporated rain — as a binary state — as an influential predictor, such that if it is raining, the likelihood of opening a window decreases. All selected models define windows as binary actuators (fully open or fully closed).

Schiavon and Lee (2013)'s model predicts adaptive clothing insulation level — in terms of ASHRAE (2010)'s clothing insulation unit clo. This model predicts clothing level on workdays using the outdoor temperature in the morning and the operative temperature in the office during the day. However, it does not predict the frequency of smaller clothing adjustments during a day. These small clothing level adjustments such as loosening up a collar or rolling up a sleeve can be influential for thermal comfort (Newsham 1997; Haldi and Robinson 2011). However, a statistical model is not available for this purpose. In the current implementation, the role of the clothing model is limited to influencing the PMV ― which is an input for Rijal et al. (2008)'s window use model.

In Reinhart (2004)'s occupancy model, five different event times are predicted in the beginning of each workday. These events are: (1) arrival time at 8h00 with a standard deviation of 15 min, (2) a coffee break at 10h00 with a standard deviation of 15 min, (3) a lunch break at 12h00 with a standard deviation of 15 min, (4) a coffee break at 15h00 with a standard deviation of 15 min, and (5) departure at 18h00 with a standard deviation of 15 min. In this model, the duration of coffee breaks and the lunch break are taken as 15 min and 60 min, respectively. Wang et al. (2005)'s iteration to this modelling approach suggests that the vacancy periods can be realistically approximated with an exponential decay function. Thus, the duration of coffee breaks and lunch breaks are drawn from an exponential probability distribution of time-constants 15 min and 60 min, respectively — in lieu of deterministic break durations 15 min and 60 min. It should be noted that these occupancy models deterministically select the number of vacancy periods (i.e., two coffee breaks and one lunch break). In reality, the average number of intermediate vacancy periods can be as small as three or as large as nine for different individuals (Rubinstein et al. 2003). Page et al. (2008) elaborated the earlier occupancy models by incorporating the inherent randomness in occupants' mobility. Page et al. (2008)'s occupancy model inputs two parameters to predict the likelihood of an arrival or a departure event: (a) the profile of probability of presence during a week and (b) the parameter of mobility. The first parameter can be generated from an observational dataset or it can be selected based on modellers prior knowledge (e.g., from modelling guidelines ASHRAE (2013)). The second parameter represents the ratio of the simulation time-steps with an occupancy state-transition (e.g., arrivals/departures including the intermediate arrivals/departures) and it accounts for the simulated occupant's tendency to take intermediate breaks.

Central to the stochastic occupancy modelling in BPS-based design is the notion that uncertainties for an occupant's presence can be added to deterministic schedules emerging from prior knowledge of the modeller — not to invent an occupancy scheme that works in every building. For the current work, it is therefore necessary to appreciate the fact that the mean event times (arrival, breaks, departure) and time constants for the vacancy periods serve only for an illustrative purpose and they are contextually restricted. While using the occupancy models shown in the current study, BPS modellers should choose appropriate model inputs using their prior knowledge. In controls-oriented modelling applications, the prior knowledge can emerge from the data gathered in the modelled building. In design-oriented applications, the prior knowledge can emerge from the data gathered in a similar building or from appropriate modelling guidelines (e.g., ASHRAE (2013) Standard 90.1).

# The simulation framework

The occupant models are transformed into a common simulation platform as illustrated in Figure 1. In order to create a diverse synthetic population, in the beginning of each run-time a unique simulated occupant is generated. To this end, the input parameters of the occupant models were assumed as normally distributed stochastic quantities. This assumption was made in accordance with Haldi (2013)'s approach to represent the diversity of the occupant models. Although the normality assumption has not been justified, Haldi (2013) remains as the only article specifically addressing diversity of the occupant models.

First, the mean occupancy state-transition times and the mean break durations are sampled from a normal distribution for occupant *i*. Table 2 presents the distribution of these values in the form of mean ± standard deviation. Once the parameters defining the occupancy habits of occupant *i* are defined in the beginning of the run-time, the occupant *i*'spresenceschedule is simulated dynamically. Note that if the arrival time is sampled as 7h30 for occupant *i*, this does not imply that occupant *i* will always arrive at 7h30. It rather implies that this occupant‘s mean arrival time is 7h30. If Wang et al. (2005)'s model is employed, the coffee and lunch break durations are generated in the beginning of each workday by employing an inverse transform sampling from an exponential distribution, as follows:

 (1)

where *τbreak* is the simulated break duration, *r* is a uniformly distributed random number between 0 and 1, and *μbreak* is the mean break duration (a coffee or a lunch break from Table 2) for occupant *i*. When Page et al. (2008) model is employed, the probability of an occupancy state-transition is approximated at each time-step as follows:

 (2)

where *x*1 is the parameter of mobility. It represents the ratio of the time-steps with an occupancy state-transition. It is randomly generated in the beginning of each runtime and remains constant for occupant *i* during the annual simulation(see Table 2). The parameter *x*2,*t*is the mean profile of probability of presence at time *t*.

C:\Users\Burak\Desktop\Carleton\Figure 2.tif

Figure 1: A simulation framework for occupant models.

Table 2: Occupancy state-transition times and vacancy durations (Reinhart 2004; Wang et al. 2005; Page et al. 2008).

|  |  |
| --- | --- |
| Arrival time (h) | 8±0.25 |
| Coffee break 1 time (h) | 10±0.25 |
| Lunch time (h) | 12±0.25 |
| Coffee break 2 time (h) | 15±0.25 |
| Departure time (h) | 18±0.25 |
| Coffee break durations (h) | 0.25±0.1 |
| Lunch break durations (h) | 1±0.25 |
| Mobility parameter | 0.25±0.25 |

In the beginning of each run-time, parameter inputs for the model predicting the clothing insulation characteristics of occupant *i* is generated from a normal distribution. Table 3 presents the distribution of these parameters in the form of mean ± standard deviation. Once the parameters defining the clothing habits of occupant *i* are defined in the beginning of the run-time, during the simulation the occupant *i*'s clothing insulation level is selected on each workday. By employing the empirical relationships developed by Schiavon and Lee (2013), the clothing insulation level during a workday is estimated as follows:

 (3)

where *clo* is the clothing insulation unit of ASHRAE Standard 55 (2010). The parameters *c*, *m*, *n* are the input parameters for occupant *i* and *x*1 and *x*2 are the predictors for the model (see Table 3). It is worth noting that this model assumes occupants' clothing levels as a continuous quantity; meaning that occupants dynamically change their clothing level in each time-step in response to a change in the operative temperature. In reality, office occupants, once they are at work, can only make discrete levels of clothing level adjustments. Contradicting to this assumption, the evidence suggests that occupants rarely undertake clothing level adjustments during a day (less than two adjustments per year according to Haldi and Robinson (2011)).

Table 3: Input parameters for the clothing insulation model (Schiavon and Lee 2013).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| c | m | n | x1 (°C) | x2 (°C) |
| 0.21±0.10 | ˗0.016±0.010 | ˗0.0063±0.0003 | Outdoor temperature at 6h00 | Operative temperature |

In the beginning of each run-time, parameter inputs for the behaviour models predicting the likelihood of an adaptive occupant action over lights, blinds, and windows are generated from a normal distribution. These parameters are inputs for the models that mimic the behavioural tendency of occupant *i* in using lighting, blinds, and windows. Tables 4 and 5 present the distribution of these parameters in the form of mean ± standard deviation.

Once the parameters representing the behaviour models for occupant *i* are generated, the likelihood of undertaking these behaviours in the next time-step (i.e., discrete-time Markov) or finding an adaptive state in the active position (e.g., open windows, switched-on lights, closed blinds) (i.e., Bernoulli) are computed during the simulation via a logistic function as follows:

 (4)

where *a* and *b*1*,..,k* are the parameters of the models, *x*1*,..,k*are the predictors of the models. The predictors can be continuous sensory measurements such as indoor temperature or workplane illuminance, or they can be binary indicators such as the occurrence of rain (Haldi and Robinson 2011). The variable *S* in Eqn. (3) stands for the adaptive state (i.e., lighting, blinds, and window) and *t* stands for the time-step index. Note that Newsham (1994)'s and Reinhart (2004)'s blinds use models were originally derived as deterministic step-functions. In an effort to maintain a consistent simulation framework, these deterministic models were smoothened analytically as a logistic function.

During a simulation, when Eqn. (3) is invoked, a random number is sampled from a uniform distribution [0,1]. This number is then compared to the likelihood estimate from Eqn. (3). If the likelihood estimate exceeds the random number, the occupant action is predicted. These random processes, once incorporated in a discrete time simulation, yield time-step size dependent solutions. Therefore, a time-step size was prescribed in most of the reviewed occupant models (typically 5 minutes). There were two exceptions to calling the behaviour models in every time-step: (a) calling after a change in the indoor climate and (b) calling after a change in the occupancy state. Rijal et al. (2008)'s model was invoked only when the predicted mean vote (PMV) falls below -0.5 or rises above +0.5. In Newsham (1994)'s and Reinhart (2004)'s blind use models, simulated occupants are only permitted to open their blinds in the time-step after arrival. Similarly, in Reinhart (2004)'s light use model, the switch-off actions are only permitted in the time-step before departure. Tables 4 and 5 also present a summary of the time instants during which these occupant behaviour models are invoked during a simulation.

Table 4: Parameters used in the lighting and blinds use models.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Occupant behaviours** | **Models** | **a** | **b1** | **b2** | **x1** | **x2** | **Calling Point** |
| Predicting light switch-on action | Hunt (1979) | 2±0.2 | ˗0.018±0.004 | ― | Workplane illuminance | ― | At arrival and in the end of the lunch break |
| Reinhart (2004) | 1.6±0.3 | ˗0.009±0.002 | ― | Workplane illuminance | ― | At arrival |
| ˗3.9±0.5 | ˗0.002±0.0005 | ― | Workplane illuminance | ― | During intermediate occupancy at 5 min time-step size |
| Predicting light switch-off action | Boyce et al. (2006) | ˗4.0±0.8 | 0.006±0.001 | ― | Workplane illuminance | ― | During Intermediate occupancy at 5 min time-step size |
| Reinhart (2004) | ˗1.3±0.3 | 0.003±0.001 | ― | Duration of absence | ― | At departure and lunch break |
| Predicting blinds closing action | Reinhart (2004) | ˗610±120 | 14.4±2.9 | ― | Direct solar irradiance on the workplane | ― | During intermediate occupancy at any time-step size |
| Newsham (1994) | ˗1450±250 | 6.5±1.3 | ― | Transmitted direct solar irradiance | ― | During intermediate occupancy at any time-step size |
| Haldi and Robinson (2010) | ˗7.4±0.16 | 0.0010±0.0001 | 2.17±0.16 | Workplane illuminance | Unshaded window fraction | At arrival |
| ˗8.0±0.1 | 0.0008±0.0001 | 1.27±0.09 | Workplane illuminance | Unshaded window fraction | During intermediate occupancy at 5 min time-step size |
| Predicting blinds opening action | Reinhart (2004) | Probability of opening the blinds is 1 at arrival | | | | | |
|  |
| Newsham (1994) |
| Haldi and Robinson (2010) | ˗1.5±0.1 | ˗0.0007±0.00005 | ˗3.14±0.07 | Workplane illuminance | Unshaded window fraction | At arrival |
| ˗3.6±0.03 | ˗0.0003±0.00002 | ˗2.7±0.04 | Workplane illuminance | Unshaded window fraction | During intermediate occupancy at 5 min time-step size |

Table 5: Parameters used in the window use models.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Occupant behaviours** | **Models** | **a** | **b1** | **b2** | **b3** | **x1** | **x2** | **x3** | **Calling Point** |
| Predicting window position | Haldi and Robinson (2008) | -1.12± 0.15 | 0.05± 0.01 | ― | ― | Outdoor temp | ― | ― | At each simulation time-step |
| Predicting window opening action | Rijal et al. (2008) | ˗6.40±1.30 | 0.17 ±0.03 | 0.17 ±0.03 | ― | Indoor temp | Outdoor temp | ― | When operative temperature is more than 2°C larger than the operative comfort temperature |
| Haldi and Robinson (2009) | ˗12.0±0.40 | 0.31 ±0.02 | 0.043±0.003 | ˗0.45±0.11 | Indoor temp | Outdoor temp | Rain | At arrival |
| ˗12.20±0.30 | 0.28 ±0.01 | 0.027±0.002 | ˗0.34±0.08 | Indoor temp | Outdoor temp | Rain | During intermediate occupancy at 5 min time-step size |
| Yun and Steemers (2008) | ˗4.80±1.10 | 0.22 ±0.05 | 0.003±0.038 | ― | Indoor temp | Outdoor temp | ― | At arrival, when the outdoor temperature is higher than 15°C |
| 0.57±8.40 | ˗0.26±2.46 | ― | ― | Indoor temp | ― | ― | During intermediate occupancy at 5 min time-step size, when the outdoor temperature is higher than 15°C |
| Predicting window closing action | Rijal et al. (2008) | 6.40±  1.30 | ˗0.17±0.03 | ˗0.17±0.03 | ― | Indoor temp | Outdoor temp | ― | When operative temperature is more than 2°C lower than the operative comfort temperature |
| Haldi and Robinson (2009) | 4.00±0.40 | ˗0.29±0.02 | ˗0.05±0.005 | ― | Indoor temp | Outdoor temp | ― | At arrival |
| ˗1.60±0.20 | ˗0.05±0.01 | ˗0.078±0.002 | ― | Indoor temp | Outdoor temp | ― | During intermediate occupancy at 5 min time-step size |
| Yun and Steemers (2008) | 0.21±0.05 | -0.007 ±0.002 | ― | ― | Indoor temp | ― | ― | When indoor temperature is less than 30°C at 5 min time-step size |

Except Haldi and Robinson (2010)'s blinds use model, all occupant behaviour models treat lighting, blinds, and windows as binary adaptive states: e.g., lights are on or off, windows and blinds are open or closed. When a blinds closing or opening action is predicted, Haldi and Robinson (2010)'s blinds use model attempts to predict the degree of actuation as well. This is carried out via a two stage process:

(1) If a blinds opening or closing action is predicted, another Markovian state-transition model in the form of Eqn. (3) with parameters shown in Table 6 is invoked. If the likelihood predicted by the model exceeds a uniformly distributed random number between 0 and 1, occupant *i* will completely open or close the blinds.

(2) If a blinds opening or closing action is predicted but a fully opening or closing action is not predicted, the model samples a partial opening or closing increment (i.e., blinds movement in terms of the fraction of a window) from a Weibull distribution with shape parameter k and scale parameter λ (see Table 7). The shape parameter λ was defined in terms of the position of the blinds prior to the adaptive action.

In the beginning of each run time, a new simulated occupant (occupant *i*+1) is generated until a representative synthetic population size is reached.

Table 6: Parameter inputs to Haldi and Robinson (2010)'s blinds use model predicting whether or not an occupant will open or close the blinds completely.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Models | a | b1 | b2 | x1 | x2 | Calling Point |
| Fully closing | ˗0.27±0.14 | (9.1±13.3) 10-7 | ˗2.23±0.16 | Exterior horizontal illuminance | Unshaded window fraction | When a blinds closing action is predicted. |
| Fully opening | ˗0.43±0.06 | (-23±1.1) 10-6 | 1.95±0.11 | Exterior horizontal illuminance | Unshaded window fraction | When a blinds opening action is predicted. |

Table 7: Parameter inputs to Haldi and Robinson (2010)'s blinds use model predicting partial blinds movement in terms of the fraction of a window.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | k | λ | x | Calling Point |
| Partial movement | 1.708 | e-2.294+1.522x | Blind position prior to the partial movement action | When a blinds closing or opening action is predicted but a full opening or full closing is not predicted. |

# Implementation in EMS application of EnergyPlus

Figure 2.a illustrates the implementation of occupant models in the EMS application of EnergyPlus. The communication between EnergyPlus (building and HVAC model) and EMS application (occupant model) was carried out through — so called — EMS Sensors and EMS Actuators. In this study, EMS Sensors can be pictured as the environmental variables that an occupant senses, whereas the EMS Actuators can be portrayed as the building components that an occupant controls. These EMS sensors are wind speed (m/s), rain status (0 or 1), outdoor, indoor and operative temperatures (°C), transmitted direct solar irradiance and direct solar irradiance on the workplane (W/m2), and the daylight on the workplane (lux). The EMS actuators are presence, lights, windows, blinds, and clothing insulation level. These EMS actuators link to the schedule values of the EnergyPlus objects for people, lights, natural ventilation, and window shading control objects. The clothing insulation level can be used as an input to determine the PMV. Should the users download the ERL script provided as a supplemental file to this manuscript and include it to the EMS Section of their EnergyPlus model using their EnergyPlus Text Editor, they can select these occupant models from their EnergyPlus IDF Editor as shown in Figure 2.b.

Haldi and Robinson (2010)'s blinds model was designed to predict partial opening or closing actions. However, in EnergyPlus, internal shades can only be actuated as open or closed. Thus, it was necessary to discretize the window into smaller pieces in order to implement Haldi and Robinson (2010)'s model for partial openings. To this end, the exterior window was divided into four smaller vertically-stacked windows such that the blinds could be actuated in five different positions (open, 0.75 open, 0.5 open, 0.25 open, closed). This accurately portrays the impact on daylight, but may lead to error regarding the effective heat transfer of a partially open blind (i.e., the benefit of trapping air between the blind and window is reduced when the air readily mixes with the room air). Alternative to this approach, the users can choose to model a blind as fully open or fully closed by neglecting partial openings by specifying the number of window divisions in the EMS script. However, this may underpredict daylight levels, which could be inadequate even for mostly-closed blinds.

# Building model for demonstration of the occupant models

This subsection discusses the comparison of predictions made by different occupant models with each other and assesses the way these predictions influence heating, cooling, and lighting load calculations of a BPS tool. To this end, a generic building model representing a hypothetical square south-facing perimeter office in Ottawa, Ontario was developed in EnergyPlus v8.1. The simulation time-step size was 5 minutes. The floor area of the model was 25 m2 and the floor-to-floor height of the air space was taken as 3 m. The office had 15 m2 of south-facing exterior envelope area, 8 m2 of which were glazed (window-to-wall area ratio of 53%). The floor consisted of 0.1 m of concrete covered by a carpet. The ceiling slab was covered with a plenum space that is enclosed by ceiling tiles. The three interior walls of the office were treated as adiabatic. The exterior wall was assumed to have insulation of 2.5 RSI in compliance with ASHRAE (2011) for Climate Zone 6. Two different window assemblies were modelled. The first window assembly was modelled with a solar heat gain coefficient (SHGC) of 0.6, a U-factor of 2 W/m2-K, and a visible transmittance of 0.75. The second window assembly was modelled with a SHGC of 0.5, a U-factor of 1.5 W/m2-K, and a visible transmittance of 0.5. The second window assembly served the purpose of comparing the predicted impact of changing the window assembly with different lighting and blinds use models.

An ideal air-based heating and cooling system was assumed with sensible heating and cooling capacities of 1.5 kW. These values were determined based on preliminary sizing runs. On weekdays, the heating setpoint was 21°C between 8h00 and 18h00 and it was set back to 18°C otherwise. On the weekdays, the cooling setpoint was 24°C between 8h00 and 18h00 and it was set back to 27°C otherwise. The energy consumed by fans and pumps was neglected. The infiltration rate was taken as 0.2 air changes per hour (ach). Outdoor air was introduced into the office at a minimum rate of 10 l/s during the occupied hours (ASHRAE 2013). When outdoor air temperature was advantageous for sensible cooling, an economizer was assumed to increase the outdoor airflow rate to a maximum of 100 l/s. The office was assumed to be used by one occupant. When an occupant opens the window, the wind-driven natural ventilation through a single-sided opening of 0.1 m2 was computed. It was assumed that the window was located at the neutral pressure level. The opening effectiveness for the ventilation rate driven by the wind was taken as 0.55 for the perpendicular winds and 0.30 for the diagonal winds, as defined in Chapter 16 of ASHRAE (2013) Fundamentals. The lights of luminous efficacy 50 lm/W (e.g., fluorescent), when switched-on, were assumed to consume 10 W.m-2 (with a radiant fraction of 0.5) (ASHRAE 2013). The equipment power density was assumed as 140 W per occupant(with a radiant fraction of 0.3) during the occupied hours (ASHRAE 2013). The internal roller blinds were assumed with a transmittance of 0.05 and a reflectance of 0.75.

|  |
| --- |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 2.tif |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 2.tif |

Figure 2: Implementation in EnergyPlus' EMS application (a) a flow chart illustrating the data exchange between EnergyPlus and occupant models and (b) a snapshot of illustrating the list of occupant models in the EnergyPlus IDF editor.

# Results and discussion

# Window opening models

Four sets of simulated occupants were generated to test each window opening model. Each set consists of 100 simulated occupants. The size of the synthetic population was selected after investigating the mean and standard deviation of the space heating, cooling, and lighting loads at varying numbers of simulated occupants (see Figure 3).

|  |
| --- |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 3.tif |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 3.tif |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 3.tif |

Figure 3: The mean and standard deviation of the (a) cooling, (b) heating, and (c) lighting load for a synthetic population of varying size.

The first set was sampled from Rijal et al. (2008), the second set was sampled from Haldi and Robinson (2009), the third set was sampled from Yun and Steemers (2008), and the fourth set was sampled from Haldi and Robinson (2008). The blinds use, lighting use, occupancy, and clothing characteristics of all four sets were created from Haldi and Robinson (2010), Reinhart (2004), Wang et al. (2005), and Schiavon and Lee (2013), respectively. This is also summarized in Table 8.

Table 8: Occupant models used in the run-cases shown in Figures 4 to 6.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Window** | **Light switch on & off** | **Blinds** | **Clothing** | **Occupancy** |
| Rijal et al. (2008) | Reinhart (2004) | Haldi and Robinson (2010) | Schiavon and Lee (2013) | Wang et al. (2005) |
| Yun and Steemers (2008) |
| Haldi and Robinson (2009) |
| Haldi and Robinson (2008) |
| Fixed windows |

Figure 4 presents the fraction of time-steps when the window remains open in monthly intervals. Results indicate that the window opening behaviour follows a similar seasonal trend with all models where mean window opening rates peak on July. On average, Yun and Steemers (2008)'s model predicted that windows remain open for about 90% of the time in July. In contrast, this ratio was about 50% with the other three window use models. Note that Yun and Steemers (2008)'s window use model was developed based on the observations collected during a summer only, whereas the observations leading to Rijal et al. (2008), Haldi and Robinson (2008), and Haldi and Robinson (2009)'s models were collected during both winter and summer months. Therefore, Yun and Steemers (2008)'s model should not be used to predict occasional window openings during heating and shoulder seasons.

|  |
| --- |
| C:\Users\Burak\AppData\Local\Temp\Rar$DRa0.552\Monthly_Windows.tif |
| C:\Users\Burak\AppData\Local\Temp\Rar$DRa0.552\Monthly_Windows.tif |

Figure 4: Monthly window use predictions by (a) Rijal et al. (2008)'s model, (b) Yun and Steemers (2008)'s model, (c) Haldi and Robinson (2009)'s model and (d) Haldi and Robinson (2008)'s model. The straight lines represent the mean and the error bars represent the standard deviation.

Figure 5 presents the annual fraction of the time-steps when the window remains open. Results indicate that the median simulated occupant with Rijal et al. (2008)'s model kept the windows open by about 5% of the time. For the same model, the median of the upper quartile was at 35%. This suggests that the predicted window opening rate shows a great variance between different simulation cases (i.e., simulated occupants). In contrast, Yun and Steemers (2008), Haldi and Robinson (2008), and Haldi and Robinson (2009)'s models predicted a smaller individual variance in window opening behaviour.

C:\Users\Burak\Dropbox\Occupant_Modelling\Windows.tif

Figure 5: Annual window use predictions.

The window opening behaviour plays an unprecedented role over the space heating and cooling loads. If occupants choose to open their windows when the ambient conditions are advantageous, this will reduce the space cooling load. If they choose to open their windows during the heating season, this will increase the space heating load. To assess the design decision support consistency, the space heating and cooling loads of the BPS model described in section 2.4 were estimated with four different window opening models and with fixed windows. Results shown in Figure 6 indicates that when occupant control of operable windows was modelled with Rijal et al. (2008), Haldi and Robinson (2008) or Haldi and Robinson (2009)'s models, the space heating load was predicted to increase by about 4 to 8% and the space cooling load was predicted to decrease by about 15 to 20%. When Yun and Steemers (2008)'s model was employed, the operable windows were predicted to increase the heating load by about 15% and to decrease the cooling load by about 40%. Although the impact of occupant use of operable windows appears to change between different window use models, all four models consistently predicted that the reduction in cooling loads with the use of operable windows will be about three times larger than the increase in heating loads for this particular BPS model.

|  |
| --- |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Windows.tif |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Windows.tif |

Figure 6: Heating and cooling load predictions by employing different window use models.

# Electric lighting and blind use models

The electric lighting models input the workplane illuminance which is also influenced by the position of the blinds. As a result, a simulated occupant's control of lights can be influenced by the choice of both blinds and lighting use model. Therefore, for three different blinds and four different light use models twelve sets of 100 simulated occupants were created (see Table 9).

Figure 7 shows that the mean hourly lighting load predictions with the occupant models do not follow a consistent pattern. When Hunt (1979)'s light switch-on model is employed, the lighting load tends to peak earlier in the day; whereas when Reinhart (2004)'s light switch-on model was employed the lighting load tends to peak later in the day (at arrival after the last coffee break). When Reinhart (2004)'s light switch-off model was employed, occupants tend to turn off their lights prior to departure in about 95% of the times. In contrast, when Boyce et al. (2006)'s model is employed, simulated occupants exhibit a greater tendency to forget their lights on prior to departure. This can be explained with the fact that occupants defined by the Boyce et al. (2006)'s model decide whether or not to turn off their lights based on the workplane illuminance ― which tends to be not high enough to trigger the light switch-off behaviour upon departure. In line with Reinhart (2004)'s interpretation about the light switch-off behaviour, Pigg et al. (1996) and Reinhart and Voss (2003) reported that the vast majority of the light switch-off actions take place just before departure and its likelihood is a function of the vacancy period followed by this departure. Therefore, Reinhart and Voss (2003)'s light switch-off model appears to capture this behaviour. However, future research should further investigate the timing and cause of light switch-off behaviour.

Table 9: Occupant models used in the run-cases shown in Figures 7 to 9 and Figures 13 to 15.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Blinds** | **Light switch-on** | **Light switch-off** | **Clothing** | **Occupancy** |
| Haldi and Robinson (2010) | Hunt (1979) | Boyce et al. (2006) | Schiavon and Lee (2013) | Wang et al. (2005) |
| Reinhart (2004) |
| Newsham (1994) |
| Haldi and Robinson (2010) | Hunt (1979) | Reinhart (2004) |
| Reinhart (2004) |
| Newsham (1994) |
| Haldi and Robinson (2010) | Reinhart (2004) | Boyce et al. (2006) |
| Reinhart (2004) |
| Newsham (1994) |
| Haldi and Robinson (2010) | Reinhart (2004) | Reinhart (2004) |
| Reinhart (2004) |
| Newsham (1994) |

C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 7.tif

Figure 7: Mean weekday lighting load profiles computed by employing different combinations of electric lighting and blinds use models. The straight lines represent the mean and the error bars represent the standard deviation.

Figure 8 presents the monthly lighting load profiles predicted by employing the twelve different occupant model combinations for lighting and blinds. Results indicate that the lighting load profiles exhibit a similar seasonal trend (minimum during the summer and maximum during the winter). However, the magnitude of the lighting load ratios are significantly different with different occupant models. When Reinhart (2004)'s blinds and light-switch models were employed, the minimum monthly lighting load ratio was 2% in July. In contrast, when Haldi and Robinson (2010)'s blinds use model was coupled with Hunt (1979)'s light switch-on model and Boyce et al. (2006)'s light switch-off model, the minimum monthly lighting load ratio was predicted as 15% (again in July). Figure 9 presents the annual lighting load distribution predicted by employing the twelve occupant model combinations for lighting and blinds. Results underline that model predictions can vary by a factor of five. However, they consistently provide predictions significantly lower than the reference office building lighting schedule recommended by ASHRAE Standard 90.1 (2013).

Figure 10 presents the mean weekday blind occlusion rate predicted by the three blind use models (Newsham 1994; Reinhart 2004; Haldi and Robinson 2010) at hourly intervals. Results do not follow a consistent trend. According to Haldi and Robinson (2010)'s model, the occlusion rate typically increases during the day until 15h00 and it starts decreasing thereon (until departure). On the contrary, in Newsham (1994)'s and Reinhart (2004)'s blind use model, the simulated occupants open their blinds only in the time-step following their first arrival. Thereafter, the occlusion rate can only increase or remain constant during the day.

C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 8.tif

Figure 8: Monthly lighting load profiles computed by employing different blinds and lighting use models. The straight lines represent the mean and the error bars represent the standard deviation.

C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 9.tif

Figure 9: The ratio of the times electric lighting was on during a year computed by employing different blinds and lighting use models.

C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 10.tif

Figure 10: Mean weekday blind occlusion rate computed by employing (a) Reinhart (2004)'s, (b) Newsham (1994)'s, and (c) Haldi and Robinson (2010)'s blinds use models. The straight lines represent the mean and the error bars represent the standard deviation of the blind occlusion rate.

Figure 11 presents the monthly blind occlusion rates predicted by the occupant models shown in Table 10. The results indicate that the blind occlusion rates do not exhibit a significant seasonal variation with Haldi and Robinson (2010)'s blinds use model. In contrast, the other models (Newsham 1994; Reinhart 2004) predicted that the blind occlusion rates during the heating and cooling seasons were significantly different (i.e., 0.75 in January and 0.25 in July). This can be interpreted with the fact that Newsham (1994)'s and Reinhart (2004)'s blinds use models input direct solar irradiance to predict blinds closing actions. During the cooling season, when the solar altitude is higher, the beam solar irradiance does not reach the workplane and does not trigger the blinds closing actions. Because Haldi and Robinson (2010)'s blinds use model inputs the workplane illuminance, its predictions do not strictly depend on the seasonal variations in the solar geometry. In line with Haldi and Robinson (2010)'s blind model, Mahdavi (2009) and Inoue (2003) did not observe a strong seasonal dependency on the blind occlusion rates on all facade orientation. Despite the hourly and monthly inconsistencies between blinds use model predictions, all three models were able to predict the annual blind occlusion rates consistently at about 50% (see Figure 12).

Table 10: Occupant models used in the run-cases shown in Figures 10 to 12.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Blinds** | **Light switch-on** | **Light switch-off** | **Clothing** | **Occupancy** |
| Haldi and Robinson (2010) | Hunt (1979) | Boyce et al. (2006) | Schiavon and Lee (2013) | Wang et al. (2005) |
| Reinhart (2004) |
| Newsham (1994) |

C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 11.tif

Figure 11: Monthly blind occlusion rate computed by employing (a) Reinhart (2004)'s, (b) Newsham (1994)'s, and (c) Haldi and Robinson (2010)'s blinds use models. The straight lines represent the mean and the error bars represent the standard deviation.

C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 12.tif

Figure 12: Mean blind occlusion rate distribution computed by employing three different blinds use models.

|  |
| --- |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 13.tif |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 13.tif |

Figure 13: Space heating loads predicted by employing a BPS model with a window assembly with (a) U-factor of 2 W.m-2°C-1, SHGC of 0.6, visible transmittance of 0.75 and with (b) U-factor of 1.5 W.m-2°C-1, SHGC of 0.5, visible transmittance of 0.5 with different blinds and lighting model combinations.

Occupant use of blinds and lighting ― due to their impact over daylight, solar gains and lighting load ― influences the space heating and cooling loads. If a building's design is changed, these changes can impact the way occupants interact with their blinds and lighting ― which in turn will impact the heating, cooling, and lighting loads. The BPS model described in subsection 2.4 with the twelve different blinds and lighting model combinations were simulated twice with two different window assemblies. One of them was defined with a U-factor of 2 W.m-2°C-1, SHGC of 0.6, and a visible transmittance of 0.75. The second window assembly was defined with a U-factor of 1.5 W.m-2°C-1, SHGC of 0.5, and a visible transmittance of 0.5.

A traditional BPS model would disregard the changes in the window's visible transmittance and input the identical lighting and blinds schedule (always open) for both cases as defined in ASHRAE Standard 90.1 (2013). The BPS model with these static blinds and lighting schedules suggests that employing the second window assembly will reduce the heating load by 20% and the cooling load by 15% ― note the lighting load does not change between two designs (see Figures 13 to 15). Although the change in visible transmittance does not play a role in space heating, cooling, and lighting loads with this traditional modelling approach, in reality it should influence the daylight availability and the blind occlusion rate ― which in turn influence the solar gains and lighting loads causing an unknown impact over the space heating and cooling loads.

The comparison between the BPS results shown in Figure 13.a and b indicates that using the second window assembly in lieu of the first window assembly was predicted to yield a 40% reduction in space heating loads. Note that this was only 20% when the traditional modelling approach was employed. Results shown in Figure 14 indicate that the BPS model with all twelve occupant models combinations consistently predict that cooling load reductions with the use of second window assembly would be about 40%. Results shown in Figure 15 indicate that the BPS model with the occupant model combinations consistently predict that there will be a 10 to 20% increase in lighting energy with the use of second window assembly. It is worth recalling that the ASHRAE Standard 90.1 (2013) schedule for lighting remains identical between two window design cases.

Also, the BPS model, when simulated with the static ASHRAE (2013) schedules, predicts significantly more space cooling loads and significantly less space heating loads than when it was simulated with the occupant models (see Figures 13 and 14). This can be attributed to the fact that the traditional BPS model assumes blinds were always open and predicted at least 1.5 times more lighting loads than the BPS model with the occupant models (see Figure 15). This leaves a building designer with the conclusion that credits cooling energy use reducing strategies over heating energy use reducing strategies.

|  |
| --- |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 14.tif |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 14.tif |

Figure 14: Space cooling loads predicted by employing a BPS model with a window assembly with (a) U-factor of 2 W.m-2°C-1, SHGC of 0.6, visible transmittance of 0.75 and with (b) U-factor of 1.5 W.m-2°C-1, SHGC of 0.5, visible transmittance of 0.5 with different blinds and lighting model combinations.

|  |
| --- |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 15.tif |
| C:\Users\Burak\Dropbox\Occupant_Modelling\Figure 15.tif |

Figure 15: Lighting load predicted by employing a BPS model with a window assembly with (a) U-factor of 2 W.m-2°C-1, SHGC of 0.6, visible transmittance of 0.75 and with (b) U-factor of 1.5 W.m-2°C-1, SHGC of 0.5, visible transmittance of 0.5 with different blinds and lighting model combinations.

# Unresolved issues and future work

# Implementation issues

The occupant models presented in this study were developed based on observational studies in different buildings across the globe. By combining different occupant submodels developed in different contexts, this paper implies that the occupant models are compatible with one another. This is an assumption as yet unverified.

Anecdotal observations suggest that the order of execution of occupant behaviours can influence the likelihood of undertaking an adaptive behaviour (Brager et al. 2004; Inkarojrit 2008; Andersen 2009). For example, Inkarojrit (2008) observed that the blind occlusion rates can be influenced with the position of the operable windows. However, because existing occupant models do not provide the conditional likelihoods for the adaptive behaviours, the dependency of different occupant behaviours were not explicitly captured in this implementation (Haldi and Robinson, 2008).

In some cases, occupant modelling was treated merely as a statistical data fitting project leaving perhaps the most important question unanswered: "When these models are simulated, how well can they replicate even their own observational dataset?" Regardless of the model complexity, the choice of simulation approaches plays a crucial role in predicting occupant behaviours in BPS. The model developers should find and report a suitable simulation algorithm for their models.

In this implementation, the diversity between simulated occupants was represented by assuming that the parameters defining the occupants' behaviour and presence are normally distributed. This methodology was discussed in greater detail in Haldi (2013). Alternatively, occupant behaviour and presence models could be defined for different individuals and from which different individuals could be randomly sampled during the simulation. However, many of the existing occupant models were developed by merging the observational data collected for different individuals. Consequently, this approach could not be employed for the current implementation in EnergyPlus.

In an effort to discuss the influence of the occupant models in the results of a BPS model's predictions for heating, cooling, and lighting, a generic private office space in Ottawa was built using the BPS tool EnergyPlus. Evidently, the results of this discussion can be influenced by the assumptions made while developing this model. Relative predictive performance of the occupant behaviour models may be different in other climates and for other BPS models. Results should be interpreted cautiously.

In this study, the ability of this BPS model to reach a design decision consistently with or without these data-driven occupant models was studied based on a limited number of performance metrics (e.g., heating, cooling, and lighting load distribution). The analysis could also be conducted with other performance indicators (e.g., predicted change in useful daylight illuminance or daylight autonomy upon a fenestration design change). This study also investigated the ability of different occupant behaviour models to make consistent predictions at different temporal resolutions. Beyond investigating the consistency of the occupant models' predictions, the accuracy of them could be assessed with respect to data gathered from numerous office spaces. Future work is planned to address these limitations.

In private office spaces, the occupant behaviour models were developed by observing occupants individually. In shared-office spaces, these models were developed by observing occupants as collective entities. Although it has been noted that occupants' behaviour patterns can be substantially different in shared-office spaces than private office spaces (Newsham 1997; Reinhart and Voss 2003; Haldi and Robinson 2010), existing occupant behaviour models do not make a distinction between these two groups. As a result, in this implementation occupant models represent individuals independent from each other and responsible for a particular window, window blind, and lighting.

A simple BPS model was used to discuss its predictive consistency and its ability to yield consistent design decisions when different occupant models were employed. This approach, despite being appropriate to assess heating, cooling, and lighting load predictions, does not provide any information about the sensitivity of the building-level heating, ventilation, and cooling equipment performance to the selection of occupant models. Future research should look into the effects of occupant models over the whole-building energy simulation.

# Modelling issues

The occupant models presented in this study vary considerably in their observational data collection and model verification methodologies. For example, some of the models were developed upon at least several years’ worth of data (e.g., Haldi and Robinson 2008; Page, Robinson et al. 2008; Haldi and Robinson 2009; Haldi and Robinson 2010), whereas some of the models were developed upon only several months’ worth of data (e.g., Reinhart and Voss 2003; Yun and Steemers 2008). In some cases candidate predictor variables were monitored via indoor sensory measurements (e.g., Haldi and Robinson 2008; Haldi and Robinson 2009; Haldi and Robinson 2010), and in some other cases local ambient conditions were used in simulation to compute the indoor predictor variables (Hunt 1979; Reinhart 2004). In a few cases, the predictive accuracy of the occupant models were assessed via cross-validation (e.g., Haldi and Robinson 2008; Haldi and Robinson 2009; Haldi and Robinson 2010) and their predictions were contrasted against other occupant models (e.g., Haldi and Robinson 2009). This underlines the need for a set of guidelines for collecting observational data, model development and verification.

Inconsistencies among the predictions of different occupant models typically arose, when models attempted to predict light switch-off or blinds opening actions. It is crucial to note that occupants typically have very little motivation to undertake these actions. Occupants' light switch-on or blinds closing actions are triggered by visual discomfort, whereas the reversal of these actions can be prompted with rather abstract concepts: 'switching off lights to be energy conscious' or 'opening blinds to regain view and connection to outdoors'.

Newsham (1994)'s model inputs transmitted direct solar irradiance to predict an occupant's blinds closing action. Although transmitted direct solar irradiance should correlate to the light intensity distribution at a cubicle, the illuminance at the cubicle should be influenced with the size and optical properties of the window. This undermines the transferability of this model to buildings with different windows.

All three blind use models (Newsham 1994; Reinhart 2004; Haldi and Robinson 2010) were developed based on observations of near-south-facing offices and have not been validated for other orientations. Inoue (2003) reported that, not only was blind occlusion a function of orientation, but daily opening and closing patterns clearly followed the sun (e.g., east-facing occupants closed blinds in the morning and opened them in the afternoon). Observational studies of offices facing other orientations would be useful.

Window use models (Rijal et al. 2008; Yun and Steemers 2008; Haldi and Robinson 2009) were developed based on observations of offices without mechanical ventilation systems. However, occupant use of windows in buildings with mechanical ventilation can be fundamentally different than it is in buildings with natural ventilation (Schweiker et al. 2011). Occupants in a building with mechanical ventilation are likely to use their windows to achieve better thermal comfort, whereas occupants in buildings with natural ventilation are likely to use them for both thermal comfort and indoor air quality related reasons.

In an early observational study conducted by Warren and Parkins (1984), it was reported that partial window openings were associated with poor indoor air quality; whereas full window openings were typically associated with thermal discomfort. They also reported that ambient noise and indoor draftiness were the primary reasons for closing windows. Future window use models can consider partial window opening and closing actions; and the role of non-temperature variables over the window use behaviour. In another observational study, Fritsch et al. (1990) observed that the window opening behaviour appeared to become independent from the outdoor temperature when it falls below 18°C. Future window use models should consider reflecting such nonlinearities, particularly for modelling window use in cold climates.

Haldi and Robinson (2010)'s blind use model was based on offices with motorized blinds with controls that favour fully open or fully closed positions. Sutter et al. (2006) found that occupants with motorized blinds move them three times as frequently as those with manually-operated blinds. Such controls can also lead to bias towards fully open or fully closed blinds since the control interfaces favour these positions. Their results could also be influenced by the peculiar façade design upon which their model is based, which features an anidolic reflector and two sets of blinds. However, Haldi and Robinson (2010)’s model is the only known model to consider partial blind opening and closing movements.

In Reinhart (2004) and Newsham (1994), occupants were modelled to open their blinds as they arrive. This almost certainly exaggerates occupants' activeness, as once occupants close their blinds it typically takes them much longer than a day to reopen them (e.g., Rubin et al. 1978; Rea 1984; O'Brien et al. 2013).

Although the evidence suggests that occupants rarely undertake major clothing level adjustments during a day, small clothing level adjustments (e.g., opening a collar or rolling up a sleeve) during a day can play a substantial role over an occupant's operative comfort temperature range (Haldi and Robinson 2011). However, a Markov transition probability for such adjustments are not available.

Some model developers tend not to report the standard error of their regression coefficients. As reported by Haldi (2013), the standard error of an occupant model's regression coefficients can provide users the information to generate a realistically diverse synthetic population — rather than exposing the error in fitting a regression model.

# Conclusions

Existing occupant models for windows, blinds, lighting, clothing, and occupancy were implemented in the EMS application of EnergyPlus. The EMS script was made publicly available.

The results predicted by different occupant models were compared with each other. The way the differences of these models influence the heating, cooling, and lighting energy computations of BPS was discussed.

Although the impact of occupant use of operable windows appears to change between the four different window use models, all four models consistently exhibit similar seasonal window opening trends and provide support for similar design decisions ― i.e., all four models consistently predicted that the reduction in cooling loads with the use of operable windows (instead of fixed windows) will be about three times larger than the increase in heating loads for a specific BPS model.

The blinds and lighting use models exhibit significant variations in their hourly and seasonal predictions. The lighting loads predicted by the twelve different blinds and lighting use model combinations varied by a factor of six. Despite this significant variation, the BPS models with different blinds and lighting use model combinations provided consistent load reduction predictions in response to a design change. In particular, for a specific BPS model with different blinds and lighting use models, substituting a window assembly with another window assembly was consistently predicted to yield a 40% reduction in the heating and cooling loads and a 10 to 20% increase in the lighting loads. In contrast, when the schedules recommended by ASHRAE (2013) were employed to represent lighting and blinds, the identical window assembly change was predicted to yield only a 15 to 20% reduction in the heating and cooling loads and no change in the lighting loads. Also, the BPS model, when simulated with the ASHRAE (2013) schedules, predicts significantly more space cooling loads and significantly less space heating loads than when it was simulated with any of the occupant model combinations.

Results of this study indicates that employing existing occupant models can be an improvement over the use of static input schedules, but future research is needed to better represent human presence and behaviour in office spaces.

**References**

Andersen, R. V. (2009). "Occupant behaviour with regard to control of the indoor environment." PhD diss., Technical University of Denmark.

ASHRAE (2010) Standard 55. "Thermal environmental conditions for human occupancy." Atlanta, American Society for Heating Refrigeration and Airconditioning Engineers.

ASHRAE (2011) Standard 140. "Standard method of test for the evaluation of building energy analysis computer programs." Atlanta, American Society for Heating Refrigeration and Airconditioning Engineers.

ASHRAE (2011) Standard 189.1. "Standard for the design of high performance, green buildings except low-rise residential buildings." Atlanta, American Society for Heating Refrigeration and Airconditioning Engineers.

ASHRAE (2013). "Handbook of Fundamentals." Atlanta, American Society for Heating Refrigeration and Airconditioning Engineers.

ASHRAE (2013) Standard 62.1. "Ventilation for Acceptable Indoor Air Quality." Atlanta, American Society for Heating Refrigeration and Airconditioning Engineers.

ASHRAE (2013). Standard 90.1. "Energy standard for buildings except low rise residential buildings." Atlanta, American Society for Heating Refrigeration and Airconditioning Engineers.

Boyce, P. R., J. A. Veitch, G. R. Newsham, C. C. Jones, J. Heerwagen, M. Myer, and C. M. Hunter. (2006). "Occupant use of switching and dimming controls in offices." *Lighting Research and Technology* 38(4): 358-376.

Brager, G., G. Paliaga, R. de Dear (2004). Operable windows, personal control and occupant comfort. *ASHRAE Transactions*, 110 (2).

Clarke, J., I. Macdonald, J. F. Nicol (2006). "Predicting adaptive responses-simulating occupied environments." International Comfort and Energy Use in Buildings Conference. Network for Comfort and Energy Use in Buildings (NCEUB), London.

D'Oca, S. and T. Hong (2014). "A data-mining approach to discover patterns of window opening and closing behavior in offices." *Building and Environment* 82(0): 726-739.

Deru, M., K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, and B. Liu (2011). "US Department of Energy commercial reference building models of the national building stock." U.S. Department of Energy. http://digitalscholarship.unlv.edu/renew\_pubs/44.

Fabi, V., R. V. Andersen, S. Corgnati, and B. W. Olesen. (2012) "Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models." *Building and Environment* 58: 188-198.

Feng, X., D. Yan, and T. Hong (2015). "Simulation of occupancy in buildings." *Energy and Buildings* 87(0): 348-359.

Fritsch, R., A. Kohler, M. Nygård-Ferguson, and J-L. Scartezzini. "A stochastic model of user behaviour regarding ventilation." *Building and Environment* 25, no. 2 (1990): 173-181.

Gunay, H. B., W. O'Brien, and I. Beausoleil-Morrison. (2013). "A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices." *Building and Environment* 70(0): 31-47.

Gunay, H. B., W. O'Brien, I. Beausoleil-Morrison, R. Goldstein, S. Breslav, and A. Khan. (2014). "Coupling Stochastic Occupant Models to Building Performance Simulation using the Discrete Event System Specification (DEVS) Formalism." *Journal of Building Performance Simulation* 7(6): 457-478.

Haldi, F. (2013). A probabilistic model to predict building occupants' diversity towards their interactions with the building envelope. Building Simulation 2013 Conference, IBPSA. France.

Haldi, F. and D. Robinson (2008). "On the behaviour and adaptation of office occupants." *Building and Environment* 43(12): 2163-2177.

Haldi, F. and D. Robinson (2008). "Stochastic / probabilistic modelling of multiple adaptive processes: some subtle complexities", eSim Conference, Quebec.

Haldi, F. and D. Robinson (2009). "Interactions with window openings by office occupants." *Building and Environment* 44(12): 2378-2395.

Haldi, F. and D. Robinson (2010). "Adaptive actions on shading devices in response to local visual stimuli." *Journal of Building Performance Simulation* 3(2): 135-153.

Haldi, F. and D. Robinson (2011). "The impact of occupants' behaviour on building energy demand." *Journal of Building Performance Simulation* 4(4): 323-338.

Haldi, F. and D. Robinson (2011). "Modelling occupants’ personal characteristics for thermal comfort prediction." International Journal of Biometeorology 55(5): 681-694.

Hoes, P., J. L. M. Hensen, M. G. L. C. Loomans, B. De Vries, and D. Bourgeois (2009). "User behavior in whole building simulation." Energy and Buildings 41(3): 295-302.

Hong, T. (2012). Occupant Behavior: Impact on Energy Use of Private Offices. Asia conference of International Building Performance Simulation Association. Shanghai, IBPSA Asia.

Hunt, D. R. G. (1979). "The use of artificial lighting in relation to daylight levels and occupancy." *Building and Environment* 14(1): 21-33.

Inkarojrit, V. (2008). "Monitoring and modelling of manually-controlled Venetian blinds in private offices: a pilot study." *Journal of Building Performance Simulation* 1(2): 75-89.

Inoue, T. (2003). "Solar shading and daylighting by means of autonomous responsive dimming glass: practical application." Energy and Buildings 35(5): 463-471.

LBNL (2013). Application Guide for EMS. Energy Management System User Guide. CA, US Department of Energy.

Mahdavi, A. (2009). "Patterns and implications of user control actions in buildings." Indoor and Built Environment. doi: 10.1177/1420326X09344277

Schweiker, M., F. Haldi, M. Shukuya, and D. Robinson. "Verification of stochastic models of window opening behaviour for residential buildings." *Journal of Building Performance Simulation* 5, no. 1 (2012): 55-74.

Newsham, G. R. (1994). "Manual control of window blinds and electric lighting: implications for comfort and energy consumption." Indoor and Built Environment 3(3): 135-144.

Newsham, G. R. (1997). "Clothing as a thermal comfort moderator and the effect on energy consumption." Energy and Buildings 26(3): 283-291.

Nghiem, T. X. (2010). MLE+: a Matlab-EnergyPlus Co-simulation Interface.

Norford, L. K., R. H. Socolow, E. S. Hsieh, and G. V. Spadaro. (1994). "Two-to-one discrepancy between measured and predicted performance of a ‘low-energy’ office building: insights from a reconciliation based on the DOE-2 model." *Energy and Buildings* 21(2): 121-131.

O'Brien, W. and H. B. Gunay (2014). "The contextual factors contributing to occupants' adaptive comfort behaviors in offices – A review and proposed modeling framework." *Building and Environment* 77: 77-87.

O'Brien, W., K. Kapsis, and A.K. Athienitis. (2013). "Manually-operated window shade patterns in office buildings: A critical review." *Building and Environment* 60: 319-338.

Page, J., D. Robinson, N. Morel, and J. Scartezzini (2008). "A generalised stochastic model for the simulation of occupant presence." *Energy and Buildings* 40(2): 83-98.

Parys, W., D. Saelens, and H. Hens (2011). "Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices – a review-based integrated methodology." *Journal of Building Performance Simulation* 4(4): 339-358.

Pigg, S., M. Eilers, and J. Reed (1996). Behavioral aspects of lighting and occupancy sensors in private offices: a case study of a university office building. ACEEE 1996 Summer Study on Energy Efficiency in Buildings

Rea, M. (1984). "Window blind occlusion: a pilot study." *Building and Environment* 19(2): 133-137.

Reinhart, C. F. (2004). "Lightswitch-2002: a model for manual and automated control of electric lighting and blinds." Solar Energy 77(1): 15-28.

Reinhart, C. F., J. Mardaljevic, and Z. Rogers (2006). "Dynamic Daylight Performance Metrics for Sustainable Building Design." *LEUKOS* 3(1): 7-31.

Reinhart, C. F. and K. Voss (2003). "Monitoring manual control of electric lighting and blinds." Lighting Research and Technology 35(3): 243-258.

Rijal, Hom B., Paul Tuohy, Fergus Nicol, Michael A. Humphreys, Aizaz Samuel, and J. Clarke. "Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings." Journal of Building Performance Simulation 1, no. 1 (2008): 17-30.

Rijal, H. B., P. Tuohy, F. Nicol, M. A. Humphreys, A. Samuel, and J. Clearke (2008). "Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings." *Journal of Building Performance Simulation* 1(1): 17-30.

Rubin, A. I., B. L. Collins, and R. L. Tibbott (1978). Window blinds as a potential energy saver: A case study, US Department of Commerce, National Bureau of Standards. https://www.ncjrs.gov/pdffiles1/Digitization/64368NCJRS.pdf

Rubinstein, F., N. Colak, J. Jennings, and D. Neils (2003). Analyzing occupancy profiles from a lighting controls field study. http://escholarship.org/uc/item/8t92v307

Schiavon, S. and K. H. Lee (2013). "Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures." *Building and Environment* 59(0): 250-260.

Schweiker, M., F. Haldi, M. Shukuya, and D. Robinson. (2011). "Verification of stochastic models of window opening behaviour for residential buildings." *Journal of Building Performance Simulation* 5(1): 55-74.

Sutter, Y., D. Dumortier, and M. Fontoynont (2006). "The use of shading systems in VDU task offices: A pilot study." *Energy and Buildings* 38(7): 780-789.

W., Danni, C. C. Federspiel, and F. Rubinstein (2005). "Modeling occupancy in single person offices." *Energy and Buildings* 37(2): 121-126.

Warren, P. R., and L. M. Parkins. "Window-opening behaviour in office buildings." Building Services Engineering Research and Technology 5, no. 3 (1984): 89-101.

Wetter, M. (2008). A Modular Building Controls Virtual Test Bed for the Integrations of Heterogeneous Systems. http://escholarship.org/uc/item/4r15r46s

Yun, G. Y. and K. Steemers (2008). "Time-dependent occupant behaviour models of window control in summer." *Building and Environment* 43(9): 1471-1482.